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Research Paper

Assessment of soil heavy metal pollution in provinces of China based on different soil types: From normalization to soil quality criteria and ecological risk assessment

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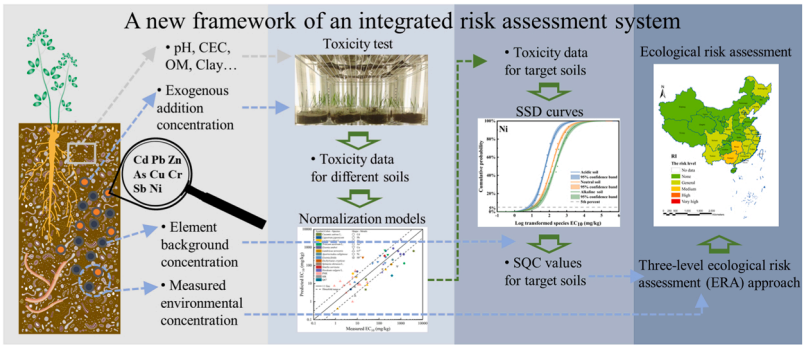
HIGHLIGHTS

- A new framework of an integrated risk assessment system was developed.
- 156 normalization models were developed for SQC and ERA based on different soils.
- Soil properties-specific and SBV-specific SQC should be considered in ERA.
- The three-level ERA for different geographic regions in China was assessed.
- As, Cr, Ni, Zn, and Cu showing a potential risk to the ecosystem in China.

GRAPHICAL ABSTRACT



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ABSTRACT

Ecological risks can vary dramatically depending on abiotic factors, such as soil properties and the background values of elements. This study developed a framework for an integrated risk assessment system to derive soil quality criteria (SQC) for heavy metals (HMs) applicable to different soil types and to assess ecological risks at a multi-regional scale. Through the construction of normalization and species sensitivity distribution models, 248 SQC values for Cd, Pb, Zn, As, Cu, Cr, Sb, and Ni in 31 Chinese provinces were derived. These SQC considered the

Abbreviations: SQC, soil quality criteria; HM, heavy metal; ERA, ecological risk assessment; DRA, deterministic risk assessment; HQ, hazard quotient; CEC, cation exchange capacity; OM, organic matter content; Clay, clay content; SSD, species sensitivity distribution; PI, the single-factor pollution index; Igeo, the geo-accumulation index; PN, the Nemerow integrated pollution index; RI, the potential ecological risk index; SBV, soil background value; PERA, probabilistic ecological risk assessment; JPC, joint probability curve; EC_{10add}, the added concentration that causes a 10 % inhibition effect on soil biota; $NOEC_{add}$, no observed effect of added concentration; $LOEC_{add}$, lowest observed effect of added concentration; HC_5, hazardous concentration for the 5 % species; MEC, measured environmental concentration; ORP, overall risk probability; DBQ, distribution-based quotient.

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Soil properties
Background values of elements
Multi-regional scale

soil types and background values of the elements and effectively reduced the uncertainty caused by spatial heterogeneity. Using the derived SQC values, the qualitative and quantitative ecological risks of HMs in the terrestrial environment of China were comprehensively assessed using a three-level ecological risk assessment (ERA) approach. Compared to traditional ERA methods, the new methodology reached a more quantitative conclusion. The mean overall probabilities of ecological risk in China were 2.42 % (Cd), 2.82 % (Pb), 12.17 % (Zn), 14.89 % (As), 10.42 % (Cu), 32.20 %(Cr), and 8.88 % (Ni). The new framework could be useful for the ERA of various soil types.

1. Introduction

With rapid economic development, soil heavy metal (HM) pollution has become increasingly prominent in China owing to its high toxicity, persistence, and irreparable damage to the ecosystem (Hu et al., 2020; Ren et al., 2022; Zhang et al., 2018). Currently, the most extensively used soil environmental quality standards in China are GB15618–2018 and GB36600–2018 for soil pollution of agricultural land and development land, respectively. Long-term research has focused on agricultural soil and development land owing to their correlation with human health (Hu et al., 2020; Liu et al., 2021; Yang et al., 2019). The ecosystem is also susceptible to metal contamination, and high HM concentrations adversely affect living organisms and ecosystem services (Chen et al., 2021; Xu et al., 2019). However, HM pollution in ecosystems has not yet received adequate attention (Wan et al., 2020). These challenges will drive government environmental management and research on HM pollution in the future.

The impact of abiotic factors (such as soil pH, cation exchange capacity [CEC], organic matter content [OM], and clay content [Clay]) on the toxicity of HMs to terrestrial organisms has been well documented, and this must be considered when developing soil quality criteria (SQC) and assessing risk (Cipullo et al., 2019; Louzon et al., 2021; Wang et al., 2022). Species sensitivity distribution (SSD) analysis is based on the statistical cumulative probability distribution of toxicity data for several species, which allows quantification of the ecological risk of pollutants from an ecosystem perspective and is therefore frequently utilised in the derivation of quality criteria (Bandeira et al., 2021; Wang et al., 2015). Simultaneously, normalization can eliminate the influence of differences in soil properties and reflect differences in species sensitivity, which is more scientific than non-normalization (Wang et al., 2018; Wan et al., 2020). The SSD method combined with normalized toxicity data of different soil properties can solve the problem of the lack of toxicity data on local species living in various ecological divisions and the influence of abiotic factors on the derivation of SQC (Ding et al., 2018; Xu et al., 2019). Moreover, the background value of soil HMs is rarely considered in the current derivation of the SQC in China (Wan et al., 2020; Yang et al., 2021). Notably, in most cases, the toxicity value used to derive ecological thresholds is the concentration of exogenous addition, while the environmental exposure value used in the risk assessment process includes the soil background value (SBV) and exogenous enrichment value, which may lead to conservative evaluation results (Ding et al., 2018). The derivation method for the ecological investigation levels (EILs) in contaminated soils in Australia explicitly considers SBVs and calculates the soil quality guideline by summing the added contaminant limit and the ambient background concentration values (NEPC, 2013a).

In the traditional deterministic risk assessment (DRA) method, the hazard quotient (HQ) model, represented by the geo-accumulation index (I_{geo}), potential ecological risk index (RI), single-factor pollution index (PI), and Nemerow integrated pollution index (P_N) methods, is widely used to determine the risk level by calculating the ratio of the predicted no-effect concentration to the exposure concentration (Xu et al., 2019; Zhang et al., 2018). The no-effect concentration of I_{geo} and RI is typically represented by the SBV, and PI and P_N can be represented by the SQC value obtained by considering environmental protection, human health, and other factors (Hu et al., 2021; Negahban et al., 2021; Xu et al., 2019). Ecological risk assessment (ERA) methods were defined using SBV and SQC as **Level 1** and **Level 2** methods in this study, respectively. The HQ approach is simple and effective for an initial screening-stage risk assessment but lacks spatial analysis of the probability and magnitude of ecological risks and does not sufficiently account for the uncertainty of environmental concentrations and species sensitivities (Shi et al., 2018, 2016). ERA based on probabilistic analysis, which assesses the risk by the probability distributions of exposure and effect, is advised for higher-level evaluation to achieve more credible risk estimates (Wen et al., 2018; Xu et al., 2019). Different from the traditional DRA method that outputs a single point value, the probabilistic ecological risk assessment (PERA) deals with the impact of uncertainty and variability on risk assessment and avoids overestimating or underestimating risks, and promotes improved risk management and decision-making (Cui et al., 2021; Shi et al., 2016; Lian et al., 2022). PERA, such as the joint probability curve (JPC) and Monte Carlo random sampling models, can offer detailed information on the probability of ecological risk (Yang et al., 2019; Shi et al., 2018), defined as the **Level 3** ERA method in this study. Recently, the application of PERA to address the uncertainty of risk assessment has become a new trend in the field of soil pollution assessment (Lian et al., 2022; Shi et al., 2016). Nevertheless, the application of probabilistic methods in soil ERA in China is considerably lower than that in aquatic environments. Few studies have focused on the ERA of HM pollution at the national scale because of the complex spatial heterogeneity, soil properties, background values of HMs, and paucity of an appropriate methodology for multi-regional scale risk assessment (Ren et al., 2022; Chen et al., 2021; Shi et al., 2016).

The major objective of this study was to develop a framework for an integrated risk assessment system to derive SQC for HMs applicable to different soil types and assess ecological risks at a multi-regional scale. The factors affecting the risk assessment results were also analysed. The new exploration could be useful for assessing ecological risk quantification from soil types and soil element background values of different regions, thus providing valuable implications and a scientific basis for mitigating the ecological risk of soil pollution.

2. Materials and methods

2.1. Overview of the framework

The developed framework of an integrated risk assessment system is shown in Fig. 1 and consists of three main stages: 1) multiple linear regression analysis and interspecies extrapolation regression were performed to establish the normalization model, and the toxicity values were normalized to the target soil conditions; 2) based on normalised toxicity data, SQC of HMs (Cd, Pb, Zn, As, Cu, Cr, Ni, and Sb) in 31 Chinese provinces were calculated by applying the SSD method and SBVs; 3) using the derived SQC, the qualitative and quantitative ecological risks of Cd, Pb, Zn, As, Cu, Cr, and Ni in the terrestrial environment of China were comprehensively assessed using the three-level ERA approach.

2.2. Development of a database for soil HM ecotoxicity

All toxicity values used to derive the SQC in this study were the

concentrations of exogenous addition. There were two sources of ecotoxicity data for soil HMs, from which the toxic effects and soil properties were determined:

a) All available and reliable toxicity data of HMs in terrestrial organisms were collected from the ECOTOX Knowledgebase (http://cfpub.epa.gov/ecotox/) and published literature. The toxicity data for clear adverse effects (such as survival, growth, and reproduction) on soil microbes, invertebrates, and plant species were selected. Additionally, the endpoints of chronic EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ were selected. All information gathered should include clear soil properties (pH, CEC, OM, and Clay). The records underneath hydroponic situations were deleted, and the data for the soil as the test medium were retained. Data on toxic effects were further processed in accordance with the guidelines below, using the geometric average values for the same toxic effect for the same species under the same soil properties.
b) In this study, 24 chronic EC_{10add} values of ecotoxicity data for two types of soils were tested to quantify the adverse effects of Cd, Cu, Pb, and As on *Lolium perenne* L. and *Medicago sativa* L. According to the standard screening of a), nine toxicity values were selected for normalisation. Text S1 and Table S1 provide the details on the toxicity test and self-measured toxicity data.

2.3. Development of a database for measured soil HM concentrations

The measured environmental concentration (MEC) data for soil HMs were also available from two sources, using strict quality control:

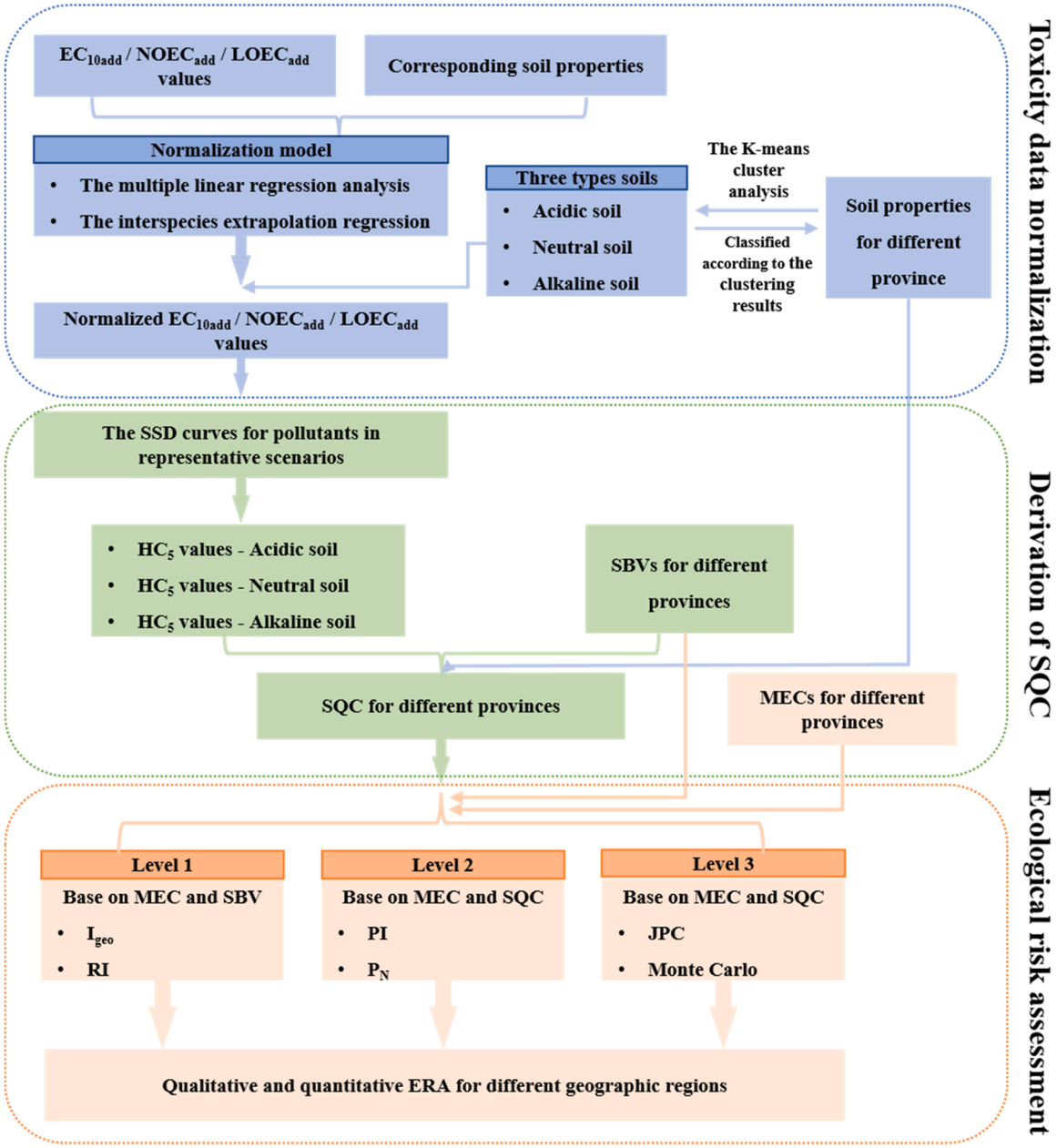

Fig. 1. The framework for integrated SQC derivation and risk assessment system. Abbreviations: EC_{10add}, the added concentration that causes a 10 % inhibition effect on soil biota; $NOEC_{add}$, no observed effect of added concentration; $LOEC_{add}$, lowest observed effect of added concentration; SSD, species sensitivity distribution; HC_5, hazardous concentration for the 5 % species; SQC, soil quality criteria; SBV, soil background value; MEC, measured environmental concentration; HM, heavy metal; PI, the single-factor pollution index; I_{geo}, the geo-accumulation index; P_N, the Nemerow integrated pollution index; RI, the potential ecological risk index; JPC, joint probability curve.

a) Most of the measured environmental concentration data were collected from the Web of Science, Elsevier Science Direct, and China National Knowledge Infrastructure databases using the keywords 'element,' 'heavy metal,' 'soil,' and 'China.' In addition, studies involving specific areas that focused on HM contamination due to accidents, or without sampling methods, processing methods, or geographical coordinates, were excluded. Multiple studies focusing on HM pollution have shown that HM concentrations in Chinese soils stabilised after 1998 (Gong et al., 2020; Li et al., 2020a, 2020b, 2021; Shi et al., 2019a, 2019b). Finally, 1088 papers that described data (1998–2021) for surface soils collected from agricultural, urban, and natural soils were retained for our analysis.
b) A total of 59 natural soil samples at a depth of 0–20 cm were collected from 2020 to 2021. The HM content analysis is presented in Text S2. The self-measured environmental concentrations of HMs in this study are shown in Table S2.

Data on HM concentrations were further processed in accordance with the guidelines below, and the geometric average values for the same HM for the different concentrations under the same or similar region were used. The number of obtained concentrations of Cd, Pb, Zn, As, Cu, Cr, and Ni were 6677, 5874, 4024, 4971, 3642, 4795, and 1272, respectively (Fig. S1).

2.4. Toxicity data normalization

Regression models should be established to normalise soil properties for species with multiple toxicity values that match the soil properties. Multiple linear regression analysis was performed to establish a regression model, and the toxicity values were normalized to the target soil conditions. The model is normally expressed as

$$\mathrm{Log}T = k_1 \bullet pH + k_2 \bullet \mathrm{Log}OM + k_3 \bullet \mathrm{Log}CEC + k_4 \bullet \mathrm{Log}Clay + b \quad (1)$$

where T is the EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ value, and k_1, k_2, k_3, and k_4 in Eq.1 are constant for the pH, CEC, OM, and Clay of soils, respectively. The R^2 and P values of the regression analysis were used to determine the effect of the multiple regression. If there were more than two toxicity values after normalization, the geometric mean value was calculated.

For species with toxic values matching soil properties that were not sufficient to establish a regression model by themselves, the interspecies extrapolation regression model was used for normalization (Wan et al., 2020; Wang et al., 2018). A single $T_{i,x}$ (T is defined in Eq.1) for a given species $_i$ in a particular test soil $_x$ was normalized to a "target soil" with properties $_y$ as follows:

$$T_{i,y} = T_{i,x} \times 10^{k_1(pH_y - pH_x) + k_2 \bullet \mathrm{Log}(OM_y / OM_x) + k_3 \bullet \mathrm{Log}(CEC_y / CEC_x) + k_4 \bullet \mathrm{Log}(Clay_y / Clay_x)} \quad (2)$$

where k_1, k_2, k_3, and k_4 are defined in Eq. 1, and from the normalised equations of species $_j$ (adopted when the taxonomic distance between species $_j$ and species $_i$ was ≤ 2). The taxonomic distance was calculated using the "Taxonomy Common Tree" of NCBI (https://www.ncbi.nlm.nih.gov) and the calculation rule was: species within the same genus: 1; family: 2; order: 3; class: 4; and phylum: 5 (Bastos et al., 2017; Raimondo et al., 2007).

Using the above normalization model, the ecotoxicity data of HMs were predicted according to soil properties and compared with the measured values (these measured values did not participate in the construction of the normalization model) to verify the prediction effect of the normalization model.

2.5. Derivation of soil quality criteria

All the HM EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ values were normalized to soil-specific properties before being used in the SSD method to fit the soil-specific SSD curves. The SSD curves of HMs were based on log-logistic functions to calculate the hazardous concentration for the 5 % species (HC_5) values. The fitting formula for the curve is as follows (Wang et al., 2015):

$$Y = 1 / (1 + \exp((P_1 - X) / P_2)) \quad (3)$$

where Y is the cumulative probability of species, defined as (the order of the data point) / (1 + total number of data points); X is the mean of the Log_{10}-transformed EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ values; and P_1 and P_2 are the parameters.

The calculation of SQC was conducted in accordance with the Australian guideline on methodology to derive EILs in contaminated soils (NEPC, 2013a). This method is predicated on the idea that a pollutant's soil background concentration is either zero or so close to it that it has no practical impact. More importantly, it is assumed that the background contributes to ecosystem biodiversity or meets the micronutrient requirements of the surrounding species (Struijs et al., 1997; NEPC, 2013a). Therefore, this approach considers only the effect of added contaminants on the environment as adverse (NEPC, 2013a). This approach is relevant for ERA and is calculated as follows:

$$SQC = SBV + HC_5 \quad (4)$$

2.6. Ecological risk assessment

The risk assessment of HMs was conducted using a three-level ERA approach. The assessment approach was as follows.

Level 1:

This includes the geo-accumulation index (I_{geo}) and potential ecological risk index (RI) which typically assess HM accumulation in soil (Liu et al., 2021; Zhang et al., 2018). The assessment involved a deterministic HQ, that is, the ratio between the MEC and SBV. The detailed calculation processes and classification criteria of I_{geo} and RI are presented in Text S3.

Level 2:

The assessment calculates the ratio between MEC and SQC to assess the ecological risk level using the single-factor pollution index (PI) and the Nemerow integrated pollution index (P_N). The detailed calculation processes and classification criteria of PI and P_N are presented in Text S4.

Level 3:

The joint probability curve (JPC) and Monte Carlo simulation have proven to be useful approaches for probabilistic risk analysis (Huang et al., 2021; Ginsberg and Giuliana, 2017; Shi et al., 2018), that can provide detailed information about the probability or magnitude of ecological risk. The JPC, constructed using the cumulative probability of toxicity data and inverse cumulative probability of exposure concentration data, reflects the probability of surpassing the contaminant concentration, generating a certain degree of ecological effect (Wen et al., 2018). The region of the JPC contained in the x-axis can be used to compute the overall risk probability (ORP) to determine the overall risk. The risk level was evaluated as negligible (ORP $<$ 0.1 %), potential (0.1 % $<$ ORP $<$ 1.0 %), or clear (ORP $\geq$ 1.0 %) (Wen et al., 2018; Cui et al., 2021). The evaluation uses Monte Carlo random sampling to determine the distribution-based quotient (DBQ) using the cumulative probability

of toxicity data and inverse cumulative probability of exposure concentration data 20,000 times. The possibility of exceeding the DBQ 0.3 served as a clear risk, and 1.0 as the potential risk (Wen et al., 2018; Ginsberg and Giuliana, 2017).

2.7. Statistical analysis

All statistical analyses were performed using SPSS v26.0 (IBM, NY, USA) and R v4.1.1, including descriptive statistical analysis, K-means cluster analysis, bivariate correlation analysis, and the normal distribution test. Monte Carlo simulations were performed using Crystal Ball 11.0. MATLAB R2013a was used to obtain the JPC. The data were analysed and mapped using Origin 2018 and ChiPlot (https://www.chiplot.online/). ArcGIS10.2 was used for the index evaluation result map.

3. Results and discussion

3.1. Toxicity data normalisation

Data from the second national soil survey in China (1982–1994) were counted, and the arithmetic means of the soil properties in each province were used for cluster analysis. Table S3 shows the soil properties of 31 Chinese provinces. The K-means cluster analysis results showed that Chinese soils can be classified into three types: acidic, neutral, and alkaline, with representative scenarios shown in Table 1 and Fig. S2. Similar clustering results have been reported in other studies (Ding et al., 2018; Wang et al., 2018). The soil properties of the 31 provinces were classified according to the clustering results (summarised in Table S3). Finally, 59 multiple regression models and 97 interspecific extrapolation regression models were developed (Table S4). All the HM EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ values were normalised using regression models and interspecific extrapolation regression models into the three representative scenarios (summarised in Table S4). For the regression model, the model prediction data were verified using the measured data and the model prediction data were found to be similar to the actual measured data (Fig. 2). Over 60 % of the predicted EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ values for the species were found to lie within a three-fold range of the measured values, 76 % within a five-fold range, and 95 % within a ten-fold range. Studies have shown that a ten-fold difference in toxicity is acceptable (Wang et al., 2020; Dyer et al., 2006). Compared to a previous study (Wang et al., 2018), models for soil invertebrates and soil microbial processes were developed in this study, and their prediction accuracy was within the acceptable range. The feasibility of normalization methods in predicting the toxicity of added Zn in soils has also been validated in previous studies (Wan et al., 2020). Normalization was an improvement for the derivation of SQC and ERA, which can eliminate the effect of differences in soil properties on toxicity. The normalized toxicity data can be applied to SQC derivation in different provinces, according to the classification results of the soil types.

3.2. Soil quality criteria of eight HMs in different Chinese provinces

The SSDs for HMs in the three soil types were constructed using log-logistic functions (Fig. 3). The sensitivity of the species is directly shown in the SSD curve. Generally, plants were more sensitive than soil animals in terms of species sensitivity, as previously mentioned by Wan et al. (2020). The species sensitivity to different HMs showed differences among the three soil types (Fig. 3). Except for As^{5+} and Cr^{6+}, the order of species sensitivity to HMs was generally acidic > neutral > alkaline, indicating that soil properties have a significant impact on the toxicity of HMs, which is consistent with Wang et al. (2018). The hazardous concentration for 5 % of the species (HC_5) in the ecosystem was calculated using SSD curves (Table S5). The HC_5 values for Pb, Cd, Cu, and Ni were notably different among the three soil types. Among them, the HC_5 value of Ni in the three soil types showed the greatest difference, approximately 2 times, i.e., between 6.59 mg/kg (acidic soil) and 13.93 mg/kg (alkaline soil). The HC_5 values of highly toxic HMs (Cd, Sb^{3+}, As^{5+}, and Cr^{6+}) were less variable (less than two-fold) in different soils.

Table 1
Three representative scenarios of Chinese soils.

Soil type	pH	CEC (cmol/kg)	OM (%)	Clay (%)
Acidic	6.31	12.48	2.08	29.52
Neutral	6.93	20.82	2.02	24.72
Alkaline	7.92	13.75	1.54	19.14

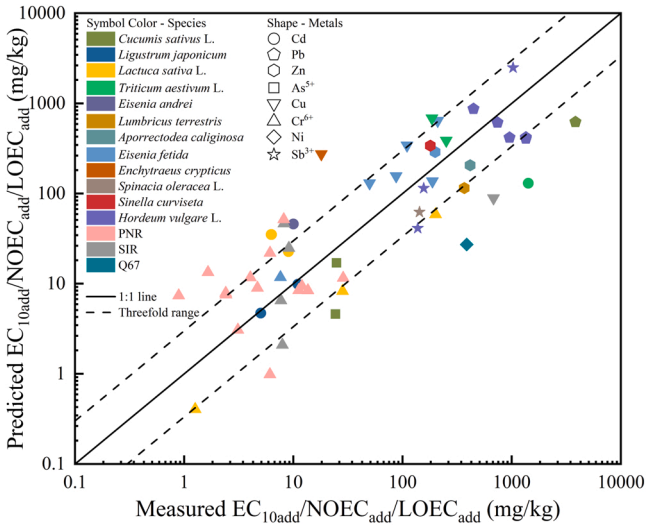

Fig. 2. Relativity between the measured and predicted EC_{10add}/$NOEC_{add}$/$LOEC_{add}$ values of heavy metals.

The Australian method of soil reference value was employed, and the soil ecological criteria values were constructed by statistical extrapolation of the effect data and an additional addition method (NEPC, 2013b). Table 2 shows the SQC developed in this study and soil quality standard values for some countries. Table S3 shows the background HM concentrations in each province used in the derivation. Because the ecotoxicity data for hexavalent chromium and pentavalent arsenic were adequate, the HC_5 values for hexavalent chromium and pentavalent arsenic were used, respectively. Owing to the differences in geographical ecology, social culture, administrative regulations, and scientific basis for the standard formulation, countries have their characteristics in formulating soil quality standard values based on soil ecological risk, resulting in differences in the names and standard values (Table 2). The U.S. ecological screening values of soil plants and soil invertebrates were derived using the geometric mean (USEPA, 2003), which was generally higher than the SQC values in this study. The EILs in Australia considered the soil background value, however, it was generally higher than the SQC values in this study, which may be caused by the lack of consideration of soil properties (NEPC, 2013b). The Netherlands soil intervention value was similar to the SQC values in this study, probably because the SSD method was adopted and the ecological receptors also included soil invertebrates, plants, and microorganisms (Anon, 2001). Except for Cd, all other SQC values were smaller than the Chinese standard values, particularly the SQC of As in Chongqing and Ni in Guangdong (more than six-fold), indicating that the SQC was more conservative. The SQC derived from different soil properties and background values of elements showed obvious differences in different regions, indicating the necessity of including soil characteristics and soil background values in the derivation process.

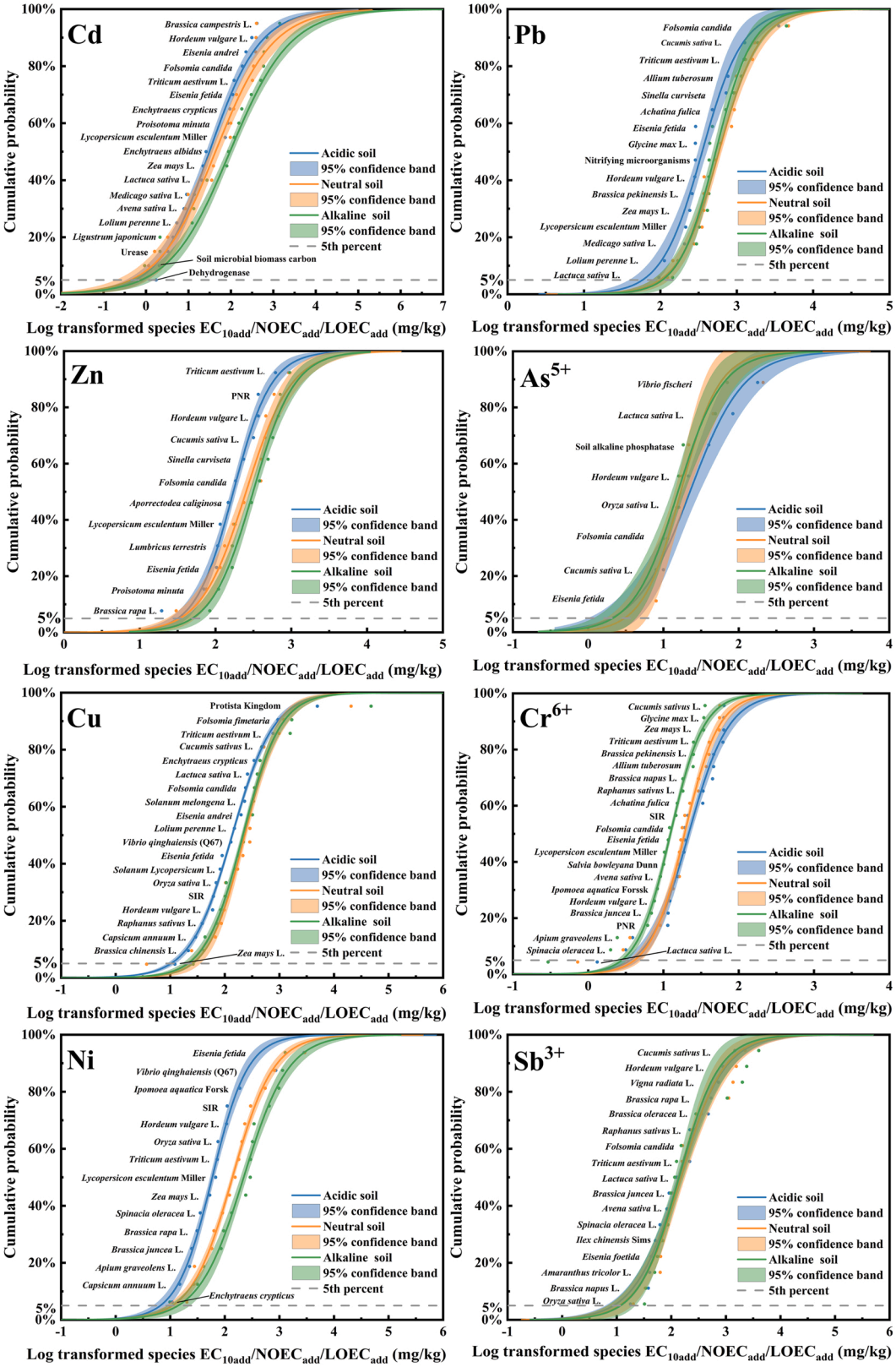

Fig. 3. The SSD curves for heavy metals in the three soil types.

3.3. Risk assessment

Based on the MEC, SBV, and SQC of HMs in 31 provinces in China, a three-level ERA approach was presented as follows:

Level 1:

Based on the MEC and SBV of HMs, Level 1 ERA was conducted using the I_{geo} and RI methods. The ecological risk of Sb was not assessed because of insufficient exposure data. The I_{geo} results showed that the percentages of uncontaminated ($I_{geo} \leq 0$) provinces were 0.06 % (Cd), 77.42 % (Pb), 64.52 % (Zn), 83.87 % (As), 54.84 % (Cu), 83.87 % (Ni),

Table 2
Comparison between the SQC developed in this study and soil quality standard values for various countries.

SQC/Standard values (mg/kg)	Region	Cd	Pb	Zn	As	Cu	Cr	Ni	Sb
SQC of 31 provinces in China	Gansu	0.89	123.99	116.38	13.84	44.45	72.09	48.33	13.76
	Ningxia	0.88	126.19	105.78	13.64	41.95	62.49	50.03	13.69
	Qinghai	0.91	126.19	125.48	15.34	42.95	69.09	42.23	13.90
	Shaanxi	0.87	126.99	115.48	12.94	41.15	63.89	41.63	13.84
	Xinjiang	0.88	125.19	115.38	12.14	46.05	50.19	39.13	13.53
	Beijing	0.49	123.59	131.05	12.46	48.55	70.82	39.07	12.20
	Hebei	0.84	126.59	121.28	14.94	42.05	68.19	42.63	13.71
	Neimenggu	0.82	121.09	97.98	8.44	33.95	39.29	31.23	13.39
	Shanxi	0.89	121.59	121.78	11.54	46.05	61.89	44.73	13.76
	Tianjin	0.53	119.29	110.55	11.96	53.05	85.52	43.67	12.30
	Heilongjiang	0.52	122.79	101.95	9.16	44.55	60.92	32.47	12.02
	Jilin	0.53	126.79	106.65	9.76	41.85	46.52	31.17	12.16
	Liaoning	0.87	126.39	109.18	10.34	39.25	56.99	37.73	13.30
	Henan	0.85	125.19	107.78	13.04	40.25	65.29	40.03	13.86
	Hubei	0.67	84.12	109.22	12.52	38.54	82.63	38.00	10.27
	Hunan	0.64	85.72	120.32	15.62	35.74	68.53	35.79	10.27
	Jiangxi	0.51	128.59	97.55	14.36	43.15	43.52	26.67	11.99
	Chongqing	0.50	119.61	79.44	5.78	38.75	43.74	23.37	12.18
	Guizhou	0.77	89.72	118.62	18.02	37.24	88.03	39.49	10.59
	Sichuan	0.52	127.79	115.95	12.36	55.15	77.82	41.97	12.25
	Xizang	0.86	133.99	120.48	18.94	40.65	70.89	42.63	13.81
	Yunnan	0.66	94.42	112.22	12.82	43.94	61.23	39.99	10.47
	Anhui	0.64	84.42	90.32	10.42	29.64	66.23	34.69	10.06
	Fujian	0.61	94.22	110.52	7.12	29.24	39.03	18.89	9.27
	Jiangsu	0.61	82.82	91.32	11.42	31.34	80.23	31.69	9.75
	Shandong	0.85	130.59	110.18	11.04	43.35	67.09	38.33	13.35
	Shanghai	0.90	130.59	129.28	9.44	47.05	71.29	42.33	13.63
	Zhejiang	0.61	81.32	94.62	9.22	24.04	45.03	28.99	9.90
	Guangdong	0.60	88.22	68.02	8.82	20.84	39.23	16.19	9.13
	Guangxi	0.64	78.92	82.52	15.42	31.74	67.93	23.99	10.84
	Hainan	0.57	117.93	111.48	8.58	42.32	64.92	41.52	12.18
	MAX	0.91	133.99	131.05	18.94	55.15	88.03	50.03	13.90
	MIN	0.49	78.92	68.02	5.78	20.84	39.03	16.19	9.13
	AVE	0.71	112.74	108.02	11.98	39.96	62.92	36.41	12.11
Standard values	Canada[a]	1.4	70	200	12	63	64	50	20
	Netherlands[b]	0.8	85	140	29	36	100	35	3
	Australia[c]	3	600	200	20	100	400	60	–
	America[d]	32/140	120/1700	160/120	18/-	70/80	-/-	38/280	-/78
	China[e]	0.3	120	250	30	100	200	100	–

[a] The Canadian standard value is the Canadian Agricultural Soil Quality Guidelines for the Protection of Environmental and Human Health from CCME (2007).
[b] Standard value of Netherlands is Dutch intervention value for agriculture and nature combines health and ecotoxicological risk criteria (Anon, 2001).
[c] Standard value of Australia is ecological investigation levels (NEPC, 2013b).
[d] According to the national standard value of the United States, we list the ecological screening values of soil plants and soil invertebrates (USEPA, 2003).
[e] Chinese standards refer to 6.5 < pH ≤ 7.5 of soil environmental quality risk control standard for soil contamination risk of agricultural land (China, 2018).

and 96.77 % (Cr) (Fig. 4. a). All areas were below moderate contamination ($I_{geo} \leq 1$), indicating that the overall accumulation of HMs in China was under a manageable level of risk, except for Cd, as mentioned by Niu et al. (2013). The RI values for the seven HMs ranged from 53.66 to 312.04 (Fig. 4. b). The percentages of no risk ($0 \leq RI \leq 150$), general risk ($150 \leq RI \leq 300$), and medium risk ($300 \leq RI \leq 600$) provinces accounted for 48.39 %, 45.16 %, and 0.06 %, respectively (Fig. 4. b), which is a completely acceptable ecological hazard, as reported by Chen et al. (2015). Nevertheless, Cd posed a potential ecological risk ($160 \leq E_r^i \leq 320$, where E_r^i is the potential ecological hazard index of the i^{th} element (Text S3)) in several provinces, particularly in Yunnan (201.18), Tianjin (210.17), Hunan (284.08), Guangdong (236.86), Zhejiang (272.04), Fujian (173.38), Heilongjiang (187.02), Beijing (171.76), Jiangxi (170.22), and Guangxi (253.91). The Level 1 risk analysis of the seven HMs showed that soil pollution was tolerable in most parts of China, except for the above ten areas.

Level 2:

The PI method can reflect the degree of pollution of each evaluation factor and rapidly determine the main pollution factors of the soil environment (Negahban et al., 2021; Xu et al., 2019). This method is typically used to assess the contribution of an individual factor because natural soil is frequently a consequence of multiple factors (Negahban et al., 2021). As shown in the results (Fig. 4. c), the order of the average single-factor pollution values was Cr (0.94) > As (0.93) > Ni (0.89) > Zn (0.83) > Cu (0.78) > Cd (0.53) > Pb (0.32), indicating that the soil was not contaminated ($P_i \leq 1$) by these HMs on average. As, Cr, Ni, Zn, and Cu have higher potential risk values than those of Cd, which differs from the Level 1 results. Furthermore, although most provinces were not polluted by these HMs at the average level, there was moderate pollution ($2 < P_i \leq 3$) for individual HMs in some regions of Southwest, East, and South China (zone division, see Fig. S3), such as the As pollution in Yunnan (2.09) and Ni pollution in Chongqing (2.14). The results of the P_N method were similar (Fig. 4. d). The spatial distribution pattern showed that the southern and eastern coastal provinces of China had relatively higher levels of soil HM contamination than those of the northern and northwestern regions. This may be due to the expanding human activities in the southern provinces and eastern coastline areas and the fact that southwest provinces constitute the main mining areas (Chen et al., 2015; Zhang et al., 2018).

Level 3:

The JPC of the 31 Chinese provinces is shown in Fig. S4. The mean ORPs were 2.42 % (Cd), 2.82 % (Pb), 12.17 % (Zn), 14.89 % (As), 10.42 % (Cu), 32.20 % (Cr), and 8.88 % (Ni), (Fig. 5. a and Fig. S4). Therefore, the chronic risk of seven metals was categorised as a clear level (ORP ≥ 1.0 %) by mean ORP, whereas Cd in Ningxia, Qinghai, Hebei, Neimenggu, Shanxi, and Hainan, Pb in Beijing, Hebei, Neimenggu, Jilin, Liaoning, Chongqing, Jiangsu, Shandong, and Hainan, and Zn in Shanxi was at a potential level (0.1 % < ORP ≤ 1.0 %), and Pb in Ningxia and

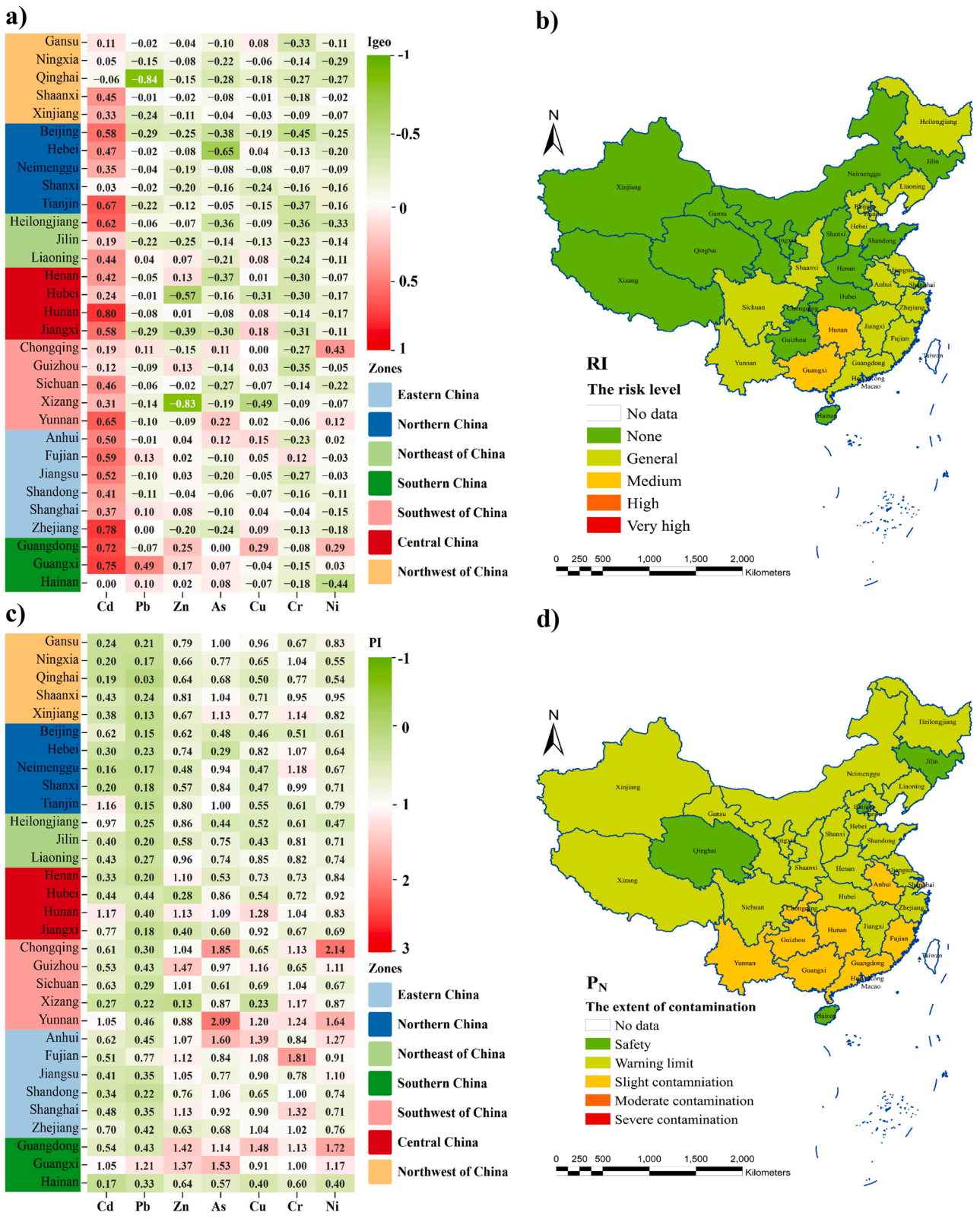

Fig. 4. The Level 1 and Level 2 ecological risk assessment results of 31 Chinese provinces. The results of a) I_{geo} and b) RI were calculated from the ratio between measured environmental concentration and soil background values, defined as the Level 1 approach; the results of c) PI and d) P_N were calculated from the ratio between measured environmental concentration and SQC in this study, defined as the Level 2 approach. Abbreviations: I_{geo}, the geo-accumulation index; RI, the potential ecological risk index; PI, the single-factor pollution index; P_N, the Nemerow integrated pollution index.

Fig. 5. The results of the JPC and Monte Carlo simulations of 31 Chinese provinces. The results of a) ORP and b) the exceedance probability for 5 % of species affected were from JPC, c) the DBQ value for clear risk and d) the DBQ value for potential risk were from Monte Carlo simulations. The size of the circle represents the exceedance probability of ecological risk. Abbreviations: JPC, joint probability curve; ORP, overall risk probability; DBQ, distribution-based quotient.

Xizang was at a negligible level (ORP < 0.1 %). The exceedance probabilities for 5 % of the affected species were quantified as 1.91–21.37 % (Cd), 0.13–73.14 % (Pb), 2.53–98.51 % (Zn), 14.1–99.38 % (As), 12.79–79.5 % (Cu), 92.28–100 % (Cr), and 5.3–64.62 % (Ni) (Fig. 5. b). Based on Monte Carlo simulations, the DBQ values for potential risk (DBQ = 1.0) were quantified as 0–7 % (Cd), 0–40.11 % (Pb), 4.34–85.49 % (Zn), 16.94–87.39 % (As), 0.02–47.5 % (Cu), 52.85–99.98 % (Cr) and 0–85.93 % (Ni) (Fig. 5. d). The DBQ values for clear risk (DBQ = 0.3) were calculated as 0–2.52 % (Cd), 0–11.54 % (Pb), 0–31.05 % (Zn), 0.078–36.64 % (As), 0–18.54 % (Cu), 10.37–59.37 % (Cr) and 0–28.41 % (Ni), respectively (Fig. 5. c).

Consistent with previous findings, the Level 1 ERA indicated that the overall accumulation of HMs in China was below a manageable risk level, except for Cd (Hu et al., 2020). The evaluation results considering SQC values (Levels 2 and 3) showed that As, Cr, Ni, Zn, and Cu had higher risk values than those of Cd, which is in accordance with previous studies (Huang et al., 2021; Shi et al., 2018; Xu et al., 2021, 2019). This differs from the Level 1 results. This may be related to the soil properties, and the background values of soil elements were considered in the calculation of SQC. A high risk of Cr and As was expected, as their SQC were derived from the toxicity data of higher toxic states. The PERA results (Level 3) showed a higher ecological risk than those in this study, as previously mentioned by Xu et al. (2019). The PERA results (Level 3) provided detailed information about the probability of ecological risk to complement the traditional DRA methods (Levels 1 and 2).

The spatial distribution pattern analysis from the all-level approach in this study implied that most of China was under a manageable risk level in the case of metal exposure. Nevertheless, the soil metal pollution in Southwest, East, and South China was relatively higher than that in the Northern and Northwestern Districts. There is evidence that acidic soils can increase the phytoavailability of certain HMs, making them easier to be absorbed by plants (Hu et al., 2020). Given that the majority of the soil in the southern provinces is naturally acidic, stronger action should be taken to address soil pollution and protect the ecosystem from hazards.

3.4. Factors influencing the ERA

Notably, the uncertainty was mainly due to the variation in the MEC; this trend appears to be common in the PERA results (Fig. 6). As Fig. 6 illustrates, data points are mainly distributed below the 1:1 line (close to the standard deviation), indicating that the high standard deviation of the exposure data significantly affects the PERA results. Multiple studies have pointed to cases in which highly polluted areas have attracted widespread attention (Hu et al., 2020; Chen et al., 2021), which might be an ineluctable cause of the high standard deviation of exposure data. Simultaneously, the low mobility of soil and unrepresentative distribution of sampling points lead to a high standard deviation of exposure data, which will lead to a deviation in the regional HM exposure distribution. Therefore, reducing the existing uncertainty and obtaining a more accurate distribution of soil metals are further problems that need to be solved.

Various anthropogenic and environmental indicators, such as resident population, gross domestic product (GDP), wastewater emissions, and soil disturbance, can reflect the degree of HM pollution in the region to a certain extent (Jiang et al., 2020; Zhang et al., 2018). The required special attention was that large-scale mining and smelting operations have greatly altered the geochemical background values of local soil HMs, and rapid economic development in coastal areas has affected the accumulation of HMs in soils (Zhang et al., 2018; Hu et al., 2020). The

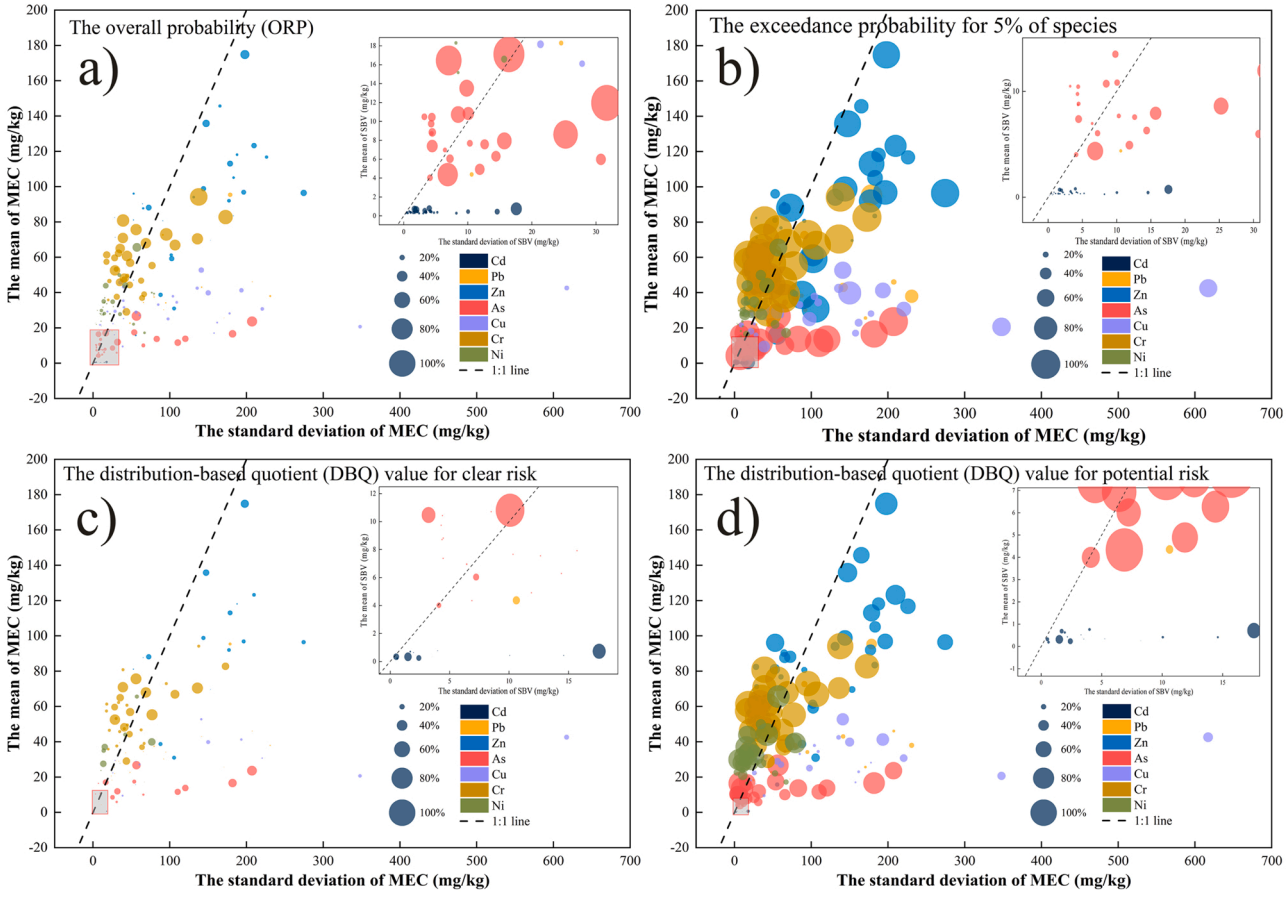

Fig. 6. The effect of standard deviation and mean values of measured environmental concentration (MEC) on the PERA results of 31 Chinese provinces. The size of the circle represents the exceedance probability of ecological risk taken from Fig. 5.

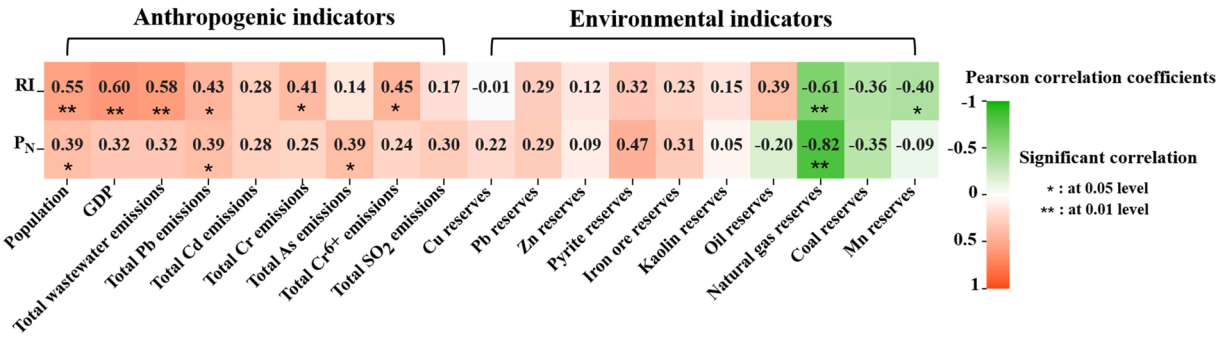

Fig. 7. The correlation between ecological risk assessment results and anthropogenic and environmental indicators was identified by combining Pearson correlation analysis. Total Pb, Cd, Cr, As, and Cr^{6+} emissions denote total Pb, Cd, Cr, As, and Cr^{6+} emissions in wastewater.

population, GDP, total wastewater emissions, HM emissions from wastewater, SO_2 emissions, and mineral reserves from 31 Chinese provinces were analysed in correlation with the RI and P_N results (Fig. 7). For more details, see Table S6. The results of this study showed that there was no significant ($P > 0.05$) positive correlation between regional soil ERA and corresponding mineral resources, but between regional soil ERA and the anthropogenic activity index (Fig. 7). This shows that anthropogenic factors have a greater impact on the environment than environmental factors. However, because regional soil HM content often shows strong spatial heterogeneity, urban development history, sampling location, and analysis errors are unavoidable influencing factors in risk assessment (Xie et al., 2019; Zhang et al., 2018).

4. Conclusions

This study demonstrated that normalized toxicity data and metal background values in different soils should be considered when deriving SQC and ERA for different geographic areas. The framework in this study highlighted that risks could change significantly depending on abiotic factors (including soil properties and metal background values). Through the normalization and SSD models, 248 SQC for Cd, Pb, Zn, As, Cu, Cr, Sb, and Ni in 31 Chinese provinces were derived in this study. The SQC in this study was lower than the Chinese standard values (except for Cd), particularly the SQC of As in Chongqing and Ni in Guangdong (more than six-fold). The results of the three-level ERA show that most of China is at a manageable risk level. The ecological risk of HMs in soils had a spatial distribution pattern, with a moderate or high risk mainly located in China's southern and eastern coastal areas and a low ecological risk in the northwestern areas. Mitigation measures for HMs in the soils of the southern and eastern coastal areas of China should be considered. The new framework proposed in this study can effectively reduce regional uncertainty and be utilised by ecological risk managers to offer insights and suggestions for the revision of soil environmental quality standards from the perspective of protecting species.

Environmental implication

Heavy metals have drawn great concern worldwide because of their highly toxic effect and ubiquity in soil. The ecological risks of hazardous metals and metalloids could vary dramatically depending on the abiotic factors, such as soil properties, element background values, etc. A new framework of an integrated risk assessment system was developed to derive soil quality criteria for heavy metals applicable to different soil types and assess ecological risks at multi-regional scales. This new framework could be useful for ecological risk assessment in multi-regional complex soil environments and will be not limited to heavy metals after development.

CRediT authorship contribution statement

Jiawen Zhang: Conceptualization, Data curation, Investigation, Methodology, Formal analysis, Validation, Visualization, Writing – original draft. **Zhengtao Liu:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing. **Biao Tian:** Methodology, Data curation, Investigation. **Ji Li:** Data curation, Resources. **Jingjing Luo:** Resources, Investigation. **Xusheng Wang:** Software, Investigation. **Shunhao Ai:** Investigation, Resources. **Xiaonan Wang:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jhazmat.2022.129891.

References

AnonRIVM, 2001. Guidance document on deriving environmental risk limits. National Institute of Public Health and The Environment, Bilthoven. ⟨http://hdl.handle.net/10029/9552⟩.

Bandeira, F.O., Alves, P.R.L., Hennig, T.B., Brancalione, J., Nogueira, D.J., Matias, W.G., 2021. Chronic effects of clothianidin to non-target soil invertebrates: ecological risk assessment using the species sensitivity distribution (SSD) approach. J. Hazard. Mater. 419, 126491 https://doi.org/10.1016/j.jhazmat.2021.126491.

Bastos, M.C., Prates, D.B., Romero, R.M., Bispo, P.C., Casatti, L., 2017. Trophic guilds of EPT (Ephemeroptera, Plecoptera, and Trichoptera) in three basins of the Brazilian Savanna. Limnologica 63, 11–17. https://doi.org/10.1016/j.limno.2016.12.004.

CCME, 2007. Canadian soil quality guidelines for the protection of environmental and human health: summary tables. Updated September, 2007. Canadian Environmental Quality Guidelines, 1999. Canadian Council of Ministers of the Environment,, Winnipeg.

Chen, H.Y., Teng, Y.G., Lu, S.J., Wang, Y.Y., Wang, J.S., 2015. Contamination features and health risk of soil heavy metals in China. Sci. Total Environ. 512–513, 143–153. https://doi.org/10.1016/j.scitotenv.2015.01.025.

Chen, X.Y., Li, F., Zhang, J.D., Liu, S.Q., Ou, C.H., Yan, J.J., et al., 2021. Status, fuzzy integrated risk assessment, and hierarchical risk management of soil heavy metals across China: A systematic review. Sci. Total Environ. 785, 147180 https://doi.org/10.1016/j.scitotenv.2021.147180.

China, 2018. Soil environmental quality: Risk control standard for soil contamination of agricultural land (GB 15618–2018). State Administration for Market Regulation Ministry of Ecology and Environment of the People's Republic of China, Beijing. Available from: ⟨http://sthjt.hubei.gov.cn/hjsj/hbbz/trhjbz/thjbz/thjgb/201807/t20180711_632826.shtml⟩. (In Chinese).

Cipullo, S., Snapir, B., Prpich, G., Campo, P., Coulon, F., 2019. Prediction of bioavailability and toxicity of complex chemical mixtures through machine learning models. Chemosphere 215, 388–395. https://doi.org/10.1016/j.chemosphere.2018.10.056.

Cui, L., Wang, X.N., Li, J., Gao, X.Y., Zhang, J.W., Liu, Z.T., 2021. Ecological and health risk assessments and water quality criteria of heavy metals in the Haihe River. Environ. Pollut. 290, 117971 https://doi.org/10.1016/j.envpol.2021.117971.

Ding, C.F., Ma, Y.B., Li, X.G., Zhang, T.L., Wang, X.X., 2018. Determination and validation of soil thresholds for cadmium based on food quality standard and health risk assessment. Sci. Total Environ. 619–620, 700–706. https://doi.org/10.1016/j.scitotenv.2017.11.137.

Dyer, S.D., Versteeg, D.J., Belanger, S.E., Chaney, J.G., Mayer, F.L., 2006. Interspecies correlation estimates predict protective environmental concentrations. Environ. Sci. Technol. 40, 3102–3111.

Ginsberg, G.L., Giuliana, B., 2017. Use of Monte Carlo analysis in a risk-based prioritization of toxic constituents in house dust. Environ. Int. 109, 101–113. https://doi.org/10.1016/j.envint.2017.06.009.

Gong, Y.W., Qu, Y.J., Yang, S.H., Tao, S.Y., Shi, T.R., Liu, Q.Y., et al., 2020. Status of arsenic accumulation in agricultural soils across China (1985-2016). Environ. Res. 186, 109525 https://doi.org/10.1016/j.envres.2020.109525.

Hu, B.F., Shao, S., Ni, H., Fu, Z.Y., Hu, L.S., Zhou, Y., et al., 2020. Current status, spatial features, health risks, and potential driving factors of soil heavy metal pollution in China at province level. Environ. Pollut. 266, 114961 https://doi.org/10.1016/j.envpol.2020.114961.

Hu, B.F., Shao, S., Ni, H., Fu, Z.Y., Huang, M.X., Chen, Q.X., et al., 2021. Assessment of potentially toxic element pollution in soils and related health risks in 271 cities across China. Environ. Pollut. 270, 116196 https://doi.org/10.1016/j.envpol.2020.116196.

Huang, J., Wu, Y., Sun, J., Li, X., Geng, X., Zhao, M., et al., 2021. Health risk assessment of heavy metal(loid)s in park soils of the largest megacity in China by using Monte Carlo simulation coupled with Positive matrix factorization model. J. Hazard. Mater. 415, 125629 https://doi.org/10.1016/j.jhazmat.2021.125629.

Jiang, Y.T., Sun, Y.J., Zhang, L.P., Wang, X.L., 2020. Influence factor analysis of soil heavy metal Cd based on the GeoDetector. Stoch. Environ. Res. Risk Assess. 34, 921–930. https://doi.org/10.1007/s00477-020-01806-z.

Li, X.Y., Zhang, J.R., Gong, Y.W., Liu, Q.Y., Yang, S.H., Ma, J., et al., 2020a. Status of copper accumulation in agricultural soils across China (1985-2016). Chemosphere 244, 125516. https://doi.org/10.1016/j.chemosphere.2019.125516.

Li, X.Y., Zhang, J.R., Ma, J., Liu, Q.Y., Shi, T.R., Gong, Y.W., et al., 2020b. Status of chromium accumulation in agricultural soils across China (1989-2016). Chemosphere 256, 127036. https://doi.org/10.1016/j.chemosphere.2020.127036.

Li, X.Y., Zhou, Y.Z., Zhang, J.R., 2021. Status and associated human health risk of zinc accumulation in agricultural soils across China. Process Saf. Environ. Prot. 146, 867–876. https://doi.org/10.1016/j.psep.2020.12.017.

Lian, Z.M., Zhao, X.M., Gu, X., Li, X.R., Luan, M.M., Yu, M., 2022. Presence, sources, and risk assessment of heavy metals in the upland soils of northern China using Monte Carlo simulation. Ecotoxicol. Environ. Saf. 230, 113154 https://doi.org/10.1016/j.ecoenv.2021.113154.

Liu, X., Chen, S., Yan, X., Liang, T., Yang, X., El-Naggar, A., et al., 2021. Evaluation of potential ecological risks in potential toxic elements contaminated agricultural soils: Correlations between soil contamination and polymetallic mining activity. J. Environ. Manag. 300, 113679 https://doi.org/10.1016/j.jenvman.2021.113679.

Louzon, M., Pauget, B., Pelfrêne, A., Gimbert, F., De Vaufleury, A., 2021. Combining human and snail indicators for an integrative risk assessment of metal(loid)-contaminated soils. J. Hazard. Mater. 409, 124182 https://doi.org/10.1016/j.jhazmat.2020.124182.

Negahban, S., Mokarram, M., Pourghasemi, H.R., Zhang, H., 2021. Ecological risk potential assessment of heavy metal contaminated soils in Ophiolitic formations. Environ. Res. 192, 110305 https://doi.org/10.1016/j.envres.2020.110305.

NEPC, 2013a. Schedule B(5)b: Guideline on methodology to derive ecological investigation levels in contaminated Soils. Amended April, 2013, In: National Environment Protection (Assessment of Site Contamination) Measure 1999. The National Environment Protection Council, Adelaide, Australia. ⟨https://www.legislation.gov.au/Details/F2013C00288/Html/Volume_7⟩.

NEPC. 2013b. Schedule B(1): Guideline on the Investigation Levels for Soil and Groundwater. Amended April, 2013, In: National Environment Protection (Assessment of Site Contamination) Measure 1999. The National Environment Protection Council, Adelaide, Australia. ⟨https://www.legislation.gov.au/Details/F2013C00288/Html/Volume_2⟩.

Niu, L.L., Yang, F.X., Xu, C., Yang, H.Y., Liu, W.P., 2013. Status of metal accumulation in farmland soils across China: from distribution to risk assessment. Environ. Pollut. 176, 55–62. https://doi.org/10.1016/j.envpol.2013.01.019.

Raimondo, S., Mineau, P., Barron, M.G., 2007. Estimation of chemical toxicity to wildlife species using interspecies correlation models. Environ. Sci. Technol. 41, 5888–5894. https://doi.org/10.1021/es070359o.

Ren, S.Y., Song, C.Q., Ye, S.J., Cheng, C.X., Gao, P.H., 2022. The spatiotemporal variation in heavy metals in China's farmland soil over the past 20 years: a meta-analysis. Sci. Total Environ. 806, 150322 https://doi.org/10.1016/j.scitotenv.2021.150322.

Shi, T.R., Zhang, Y.Y., Gong, Y.W., Ma, J., Wei, H.Y., Wu, X., et al., 2019a. Status of cadmium accumulation in agricultural soils across China (1975-2016): from temporal and spatial variations to risk assessment. Chemosphere 230, 136–143. https://doi.org/10.1016/j.chemosphere.2019.04.208.

Shi, T.R., Ma, J., Zhang, Y.Y., Liu, C.S., Hu, Y.B., Gong, Y.W., 2019b. Status of lead accumulation in agricultural soils across China (1979-2016). Environ. Int. 129, 35–41. https://doi.org/10.1016/j.envint.2019.05.025.

Shi, Y.J., Wang, R.S., Lu, Y.L., Song, S., Johnson, A.C., Sweetman, A., et al., 2016. Regional multi-compartment ecological risk assessment: establishing cadmium pollution risk in the northern Bohai Rim, China. Environ. Int. 94, 283–291. https://doi.org/10.1016/j.envint.2016.05.024.

Shi, Y.J., Xu, X.B., Li, Q.F., Zhang, M., Li, J., Lu, Y.L., et al., 2018. Integrated regional ecological risk assessment of multiple metals in the soils: a case in the region around the Bohai Sea and the Yellow Sea. Environ. Pollut. 242, 288–297. https://doi.org/10.1016/j.envpol.2018.06.058.

Struijs, J., Vande Meent, D., Peijnenburg, W., Vanden Hoop, M., Crommentuijn, T., 1997. Added risk approach to derive maximum permissible concentrations for heavy metals: How to take natural background levels into account. Ecotoxicol. Environ. Saf. 37, 112–118. https://doi.org/10.1006/eesa.1997.1534.

USEPA, 2003. Guidance for Developing Ecological Soil Screening Levels. Office of Solid Waste and Emergency Response, U.S. Environmental Protection Agency, Washington D C. ⟨https://www.epa.gov/chemical-research/guidance-developing-ecological-soil-screening-levels⟩.

Wan, Y.N., Jiang, B., Wei, D.P., Ma, Y.B., 2020. Ecological criteria for zinc in Chinese soil as affected by soil properties. Ecotoxicol. Environ. Saf. 194, 110418 https://doi.org/10.1016/j.ecoenv.2020.110418.

Wang, X.N., Liu, Z.T., Wang, W.H., Zhang, C., Chen, L.H., 2015. Derivation of predicted no effect concentration (PNEC) for HHCB to terrestrial species (plants and invertebrates). Sci. Total Environ. 508, 122–127. https://doi.org/10.1016/j.scitotenv.2014.11.079.

Wang, X.N., Fan, B., Fan, M., Belanger, S., Li, J., Chen, J., et al., 2020. Development and use of interspecies correlation estimation models in China for potential application in water quality criteria. Chemosphere 240, 124848. https://doi.org/10.1016/j.chemosphere.2019.124848.

Wang, X.Q., Wei, D.P., Ma, Y.B., McLaughlin, M.J., 2018. Soil ecological criteria for nickel as a function of soil properties. Environ. Sci. Pollut. Res. 25, 2137–2146. https://doi.org/10.1007/s11356-017-0456-6.

Wang, Y., Wang, S.J., Jiang, L., Ma, L., Li, X.Y., Zhong, M.S., et al., 2022. Does the geographic difference of soil properties matter for setting up the soil screening levels in large countries Like China? Environ. Sci. Technol. 56, 5684–5693. https://doi.org/10.1021/acs.est.1c08771.

Wen, J.J., Cui, X.Y., Gibson, M., Li, Z.Y., 2018. Water quality criteria derivation and ecological risk assessment for triphenyltin in China. Ecotoxicol. Environ. Saf. 161, 397–401. https://doi.org/10.1016/j.ecoenv.2018.06.012.

Xie, T., Wang, M.E., Chen, W.P., Uwizeyimana, H., 2019. Impacts of urbanization and landscape patterns on the accumulation of heavy metals in soils in residential areas in Beijing. J. Soil. Sediment. 19, 148–158. https://doi.org/10.1007/s11368-018-2011-6.

Xu, C., Pu, J., Wen, B., Xia, M., 2021. Potential ecological risks of heavy metals in agricultural soil alongside highways and their relationship with landscape. Agriculture 11. https://doi.org/10.3390/agriculture11080800.

Xu, X.B., Wang, T., Sun, M.X., Bai, Y.L., Fu, C., Zhang, L.X., et al., 2019. Management principles for heavy metal contaminated farmland based on ecological risk—a case study in the pilot area of Hunan province, China. Sci. Total Environ. 684, 537–547. https://doi.org/10.1016/j.scitotenv.2019.05.015.

Yang, Q., Yang, Z.F., Filippelli, G.M., Ji, J.F., Ji, W.B., Liu, X., et al., 2021. Distribution and secondary enrichment of heavy metal elements in karstic soils with high geochemical background in Guangxi. China. Chem. Geol. 567, 120081 https://doi.org/10.1016/j.chemgeo.2021.120081.

Yang, S.Y., Zhao, J., Chang, S.X., Collins, C., Xu, J.M., Liu, X.M., 2019. Status assessment and probabilistic health risk modeling of metals accumulation in agriculture soils across China: a synthesis. Environ. Int. 128, 165–174. https://doi.org/10.1016/j.envint.2019.04.044.

Zhang, X.X., Zha, T.G., Guo, X.P., Meng, G.X., Zhou, J.X., 2018. Spatial distribution of metal pollution of soils of Chinese provincial capital cities. Sci. Total Environ. 643, 1502–1513. https://doi.org/10.1016/j.scitotenv.2018.06.177.